A NEW TECHNIQUE FOR GRAPE INSPECTION AND SORTING CLASSIFICATION

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ABSTRACT

Sorting and classification of fruits are the main problem specially for Superior and King Ruby varieties which represent more than 50% of grape production in Egypt. A usual procedure to carry out this task is based on human visual inspection considering general fruit attributes like color, size, shape, firmness and sugar content of grape cluster. Color contains important information about fruit status and in some cases it is decisive for fruit quality differences. This paper provides a new technique to investigate the applicability of color classification, sugar content and firmness of grape. Standard RGB color chart, artificial neural network and a potential of near-infrared (NIR) reflectance as a means for nondestructive measurements of grape firmness and sugar content were used. NIR spectral data were collected from the two varieties of grape in the spectral region between 800 nm and 1700 nm. Statistical models were developed using the partial least square method to predict the firmness and sugar content of grape. The models gave relatively good predictions of the firmness of both Superior and King Ruby, with corresponding r values of 0.80 and 0.65. The NIR models gave excellent prediction for grape sugar content with values of 0.71 % and 0.65 % Brix for Superior and King Ruby, respectively.

Keywords: Machine vision, Grape inspection, Sorting, Sugar content

INTRODUCTION

Grape is the second important fruit in Egypt coming directly after citrus fruits. Egypt cultivates 152488 feddan of grape which produce about 1,073,815 ton as stated by the **Periodical News of Agric. Res. Center (2004)**. There are many kinds of grape cultivated in Egypt such as Superior, Perelette, Delight, Flame, Fantasy, Thompson, Fiesta, Emerald, Mellessa, Black Monnikka, King Ruby, Gold and more. The most famous and used in Egypt are Superior and King Ruby which represent more than 50% of grape production. Grapes have the highest production among fruits in the world, and most of those are produced as an ingredient of wine. In Egypt, most of them are produced as table varieties, and the big berries exceeding 12 g are the popular among consumers as the high-grade fruits for export. The cultivation of the varieties with big berries seeded is one of the most

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advanced techniques for the tree fruit production in Egypt. The main characteristics for visual inspection and classification of fruits are color, shape, firmness and sugar content.

An efficient autonomous system for fruit sorting must be able to adequately identify all parameters. image processing. Fruit shape can easily be obtained from a digital image using classical techniques for Firmness and sugar content are two important quality attributes that not only determine the consumer acceptance and shelf life of grape but also influence their susceptibility to bruising and pathogenic invasion. When a human being observes wavelengths included in the range of visible light, he immediately group them into classes, using psychological notions learned for color separations. So, the color classification process can be seen as an application of highly non-linear functions into a digital image function. A digital (discrete) image function f(x) is a mathematical representation of an image, given by $f(x,y) = \{f_{red}(x,y), f_{green}(x,y), f_{blue}(x,y)\}$, where $f(x,y)$ represents image color and brightness at a spatial coordinate (x,y), named pixel. We also have estimated the performance of the classificatory considering different color representation systems, which led us to the conclusion that the RGB color representation system is the best accuracy for classification (**Sim and Reali Costa 2000 a, b and c**).

Therefore it is necessary to take an accurate grasp of the tree growth change and to make a suitable cultivation management for the change. Cultivator has been learning to sense a delicate change of the plants through his ripe experience, which is mainly based on visual observation. So far the information visually observed by the experienced cultivator could not have been clarified because it is difficult to quantitatively evaluate the information such as the color, shape and sugar content. The purpose of this study is to propose how to utilize a popular digital camera for color evaluation by Near-Infrared (NIR) and to quantify the sugar content and coloring change with the growing of grape tree, which has been judged by visual sense of cultivator. A common, subjective method for assessing the firmness of grape is to squeeze the fruit between fingers, which is practiced by growers to make harvest decisions and by consumers when purchasing fresh grape. As the grape ripens, its skin color generally changes, for instance, from green to dark red. Researchers have developed color charts as a guide to make harvest decisions (**Timm *et al* 1995**). However, the correlations of skin color with firmness, sugar content, or other attributes (such as acid and specific gravity) are unreliable and generally low (**Mitcham *et al* 1998**). In the past, numerous nondestructive or minimally destructive techniques have been reported for measuring the firmness of grape. **Parker *et al* (1966)** compared four techniques, including two dropping and two compression techniques, for measuring the firmness of grape. They found that only the dial gauge compression technique, which measures the deformation of the grape under a constant load, was acceptable. **Younce and Davis (1995)** reported a nondestructive grape firmness device based on measuring the momentum generated from impacting the fruit onto the disc of an audio speaker. **Timm *et al* (1993)** developed a portable instrument for measuring grape firmness by compressing the fruit between two parallel

plates. **Armstrong *et al* (1995)** reported a laboratory grape firmness instrument that measures the force-deformation relation of individual grape as a firmness index. **Chen and Ruiz-Altisent (1996)** reported on a firmness device based on measuring the acceleration characteristics of a low-mass impactor upon impacting the fruit. **Mitcham *et al* (1998)** evaluated the performances of three nondestructive devices **(Armstrong *et al* 1995; Chen and Ruiz-Altisent 1996 and Younce and Davis 1995)** and a destructive penetrometer. They compared the results of these four devices with a special compression method, which uses a 9-mm diameter ball bearing to compress the fruit for 1 mm of deformation. **Mitcham *et al* (1998)** reported that the device of **Armstrong *et al* (1995)** provided the most consistent measurements among the four compared. Recently, several studies have been reported on using near-infrared (NIR) spectroscopy techniques in the spectral region between 700 nm and 1100 nm to measure the sugar content of fruits including apples, kiwifruits, melons, peaches, pears, and tangerines **(Dull *et al* 1992; Kawano *et al* 1992; Kawano *et al* 1993; Slaughter 1995 and Ventura *et al* 1998)**. Since NIR spectroscopic measurements are affected by many factors such as sensing technique and detector type, direct comparisons of these studies, to determine which spectral regions are most appropriate for sugar content and firmness measurement, are often difficult. However, a greater spectral region beyond 1100 nm appears to give improved prediction results in sugar content and other quality attributes. **Lu *et al* (2000)** conducted a study to predict the firmness and sugar content of apples in the spectral region between 800 nm and 1700 nm. They found that the technique gave good predictions of the apple's sugar content, with the standard error of prediction (SEP) ranging from 0.5 % to 0.7 % Brix. So far, no studies have been reported on using NIR techniques for measuring the firmness and sugar content of grape.

   The objective of this study is to investigate the NIR diffuse reflectance technique as a means to predict the firmness and sugar content of grape. Furthermore, the specific objectives were:

1- To measure the diffuse reflectance of grape over the spectral region between 800 nm and 1700 nm.
2- To develop statistical models from the diffuse reflectance data to predict the color, firmness and sugar content of grape.

MATERIAL AND METHODS

1. Grape Sorting and Classification

   There are many kinds of grape cultivated in Egypt such as Superior, Perelette, Delight, Flame, Fantasy, Thompson, Fiesta, Emerald, Mellessa, Black Monnikka, King Ruby, Gold and more. The most famous and used in Egypt are Superior and King Ruby which represent more than 50% of grape production so, those two varieties were chosen in this study as shown in **Fig. (1)**. According to Egyptian fruit classification patterns **(Periodical News of Food Technology Res. 2000)**, grape must be classified in several different aspects, such as size, color, sugar content, firmness and blemishes. Five different grape classes are defined: a) corresponding to dark green; b) to light green; c) to yellow; d) to light red e) to red.

a) King Ruby variety   **b) Superior variety**

Fig. 1. The two famous grape varieties cultivated in Egypt

2. Using ANN for Color Classification

Under a range of proper illumination conditions, the groups of colors (red, green, brown, etc.) can be easily separated by edges. The problem of color classification can thus be seen as a problem of determination of optimum edges capable of a suitable partition of an RGB color space. These edges capable of processing this separation have some special characteristics. The edges are not necessarily regular, and are not necessarily of same size. The edges must have some generalization level in such a way that pixels with small variations in color illuminations and saturation are evolved by the same edge. In order to fulfill these requirements, we propose the use of an artificial neural network (ANN) multilayer preceptor (MLP) trained by the back-propagation algorithm (**Sim and Reali Costa 2000 a**). In this network model, there are three input neurons (that receive the triple of color representation of each pixel in a frame), one hidden layer with 10 neurons, and 7 output classes, corresponding to white, dark green, light green, yellow, light red, dark red and blemished as a background class. To train the network we extracted some pixel examples of the typical colors using some frames with a graphical interface. A frame corresponds to a digital image of grape in white background. Once trained, the totality of pixels in a frame was presented to the network (pixel by pixel). The network returned all image pixels classifieds

as one of the system typical colors. The network classification was stored (pixel by pixel) and getting an output image from the initial frame. As shown in previous works **(Elbatawi 2004)**, simple examples of the colors without brightness or saturation examples are enough to obtain a satisfactory classification performance (about 97% with low illumination and color saturation variations) with low computational cost. The totality of pixels of grape image does not necessarily belong to the same color class. Since the model of Egyptian fruits classification was defined to color classification conducted by humans, there is no exact definition of the deviation ranges applied to each class. In order to adequately model grape classes, some typical grape (classified by humans) of each class were presented to the network (pixel by pixel). Observing its classified images, the percentage of each system color present in each grape class was obtained. So, the process of grape classification can be seen as a problem of vector approximation. The exception to this rule is the rejected grape which presents a minimum level of blemished pixels and was considered a rejected one.

3. Using Near-Infrared Diffuse Reflectance (NIR)

NIR diffuse reflectance measurements were performed using an Oriel system. The system consisted of a DC light source with the control unit, and a thermal electric cooled detector connected to an Oriel controlling/amplifying unit, which in turn was connected to a computer. A 250 W quartz tungsten halogen lamp was used to provide broadband light, which was modulated by a chopper at 60 Hz. The light was delivered to the fruit through a guide cable to capture the images. The diffusely reflected light was acquired by a fiber optic detector and sent to the Oriel system where the light was dispersed according to the wavelength. The dispersed light at different wavelengths was sensed by the detector and converted into electronic signals to the computer. In this study, the light delivery probe was oriented 45° from the sensing probe as shown in **Fig. (2).**
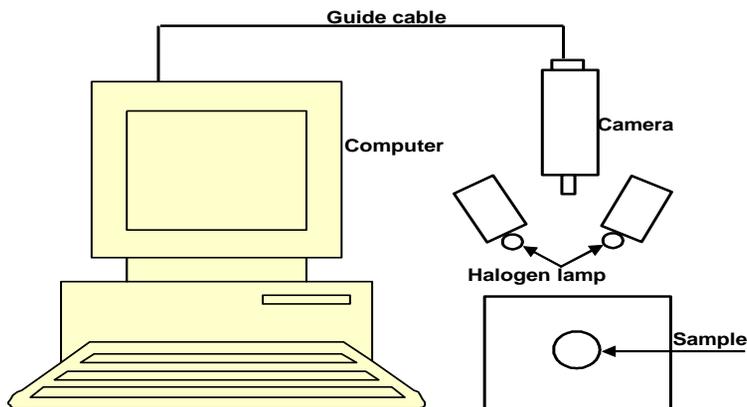

Fig. 2. Schematic diagram of image system

Each test grape cluster was placed in the sample holder with a 15mm diameter hole. The berry was positioned with the distal side and facing down towards the light delivery probe. One scanning was performed for each fruit between 800 nm and 1700 nm at an interval of 2 nm. NIR was used to detect both sugar content and firmness. The obtained sugar content data by NIR was used to compare it with the one measured by HPLC instrument. The HPLC instrument was equipped by 1100 series agilent pump, auto sampler HP 1050 and reflective index detector HP 1047A attached with personal computer. On the other hand, LFRA Texture Analyzer (2mm and 5mm depth) was used to measure the firmness of grape berries. Both used instruments were located at Food Technology Research Institute, Agricultural Research Center, Giza, Egypt.

4. Image analysis

The first step of image analysis is to select image elements (pixels) which belongs to grape clusters. The background and pores of grape presents a luminance level of 250pixels which means low luminance level. The segmentation was done with a threshold which allow to keep the darker part of the image. The threshold result was a binary image.

4.1. Acquisition of Grape Cluster Image

Grape cluster images of the two varieties were taken by a digital camera from the grape field at North Tahrir Agriculture Company (south of Alexandria). Three kinds of images were acquired for each period of early coloring stage in June, 2005, coloring anaphase in July, 2005 and harvest time in August, 2005. The digital camera (DS-400, Canon Photo Film), which has 1.3 million-pixel CCD and a function of adjusting the white balance, was used for image acquisition. The acquired digital image data taken under the conditions that the squeezing value and shutter speed were automatically fixed and accumulated in the memory card of the digital camera. Five fruit clusters were chosen from each tree, which have different 4 steps of bearing stress. The images taken from the north, south, east and west in 3 periods were acquired. Image was captured from vertically held fruit in order to avoid hazardous berries inside the grape. Berries in the cluster depend on the way the operator lead the fruit down. In this case a bias could occur during the compactness measurement. Grape cluster was hanged up in front of an enlightening surface. This background lighting allowed to reveal the grape cluster porosity. Front lighting was insured with two neon lightings. The CCD camera was mounted at a distance of 50 cm from the enlightening surface and the size of grape cluster image was 512x512 pixels. The obtained data was compared by the one measured using a Hunter-lab D25L optical sensor located at Food Technology Research Institute, Agricultural Research Center, Giza, Egypt.

4.2. Peduncle elimination

The berries of grape are the main object to be captured. So, a successive erosion-dilatation was used to eliminate the peduncle in the grape cluster. After filling the grape by erosion-dilatation, a single object without pores was captured. This

elimination was allowed to measure all shape features like area, main diameters in X and Y directions, perimeter and convex perimeter. The porosity was obtained by subtracting the filled image to the initial one.

4.3. Location of berries inside the contour

The diameter measurement of berries inside the grape cluster was estimated by sampling berries of the contour of the grape. Once the contour of the grape was isolated, each arc of circle corresponded to each isolated berry. This segmentation was performed by removing points of high curvature in the contour (critical points) as shown in **Fig. (3)**.

4.4. Location of berries inside the grape cluster

Berries inside the grape cluster present rings of specular reflexion due to frontal lighting and spherical shape of berries. The number and relative density of berries inside grape cluster was one of the features that characterize grape compactness. The number of specular reflexion rings were isolated and noted during image processing as shown in **Fig. (4)**.
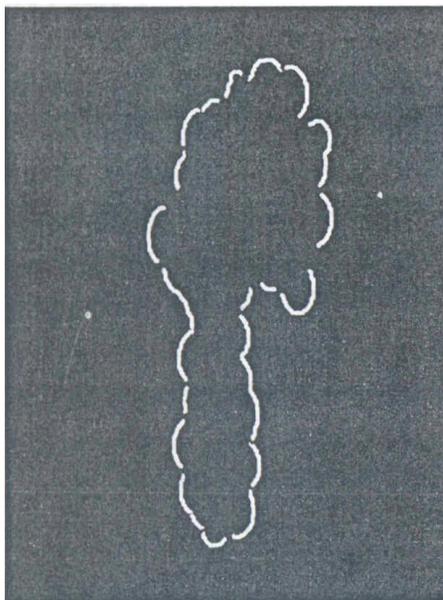

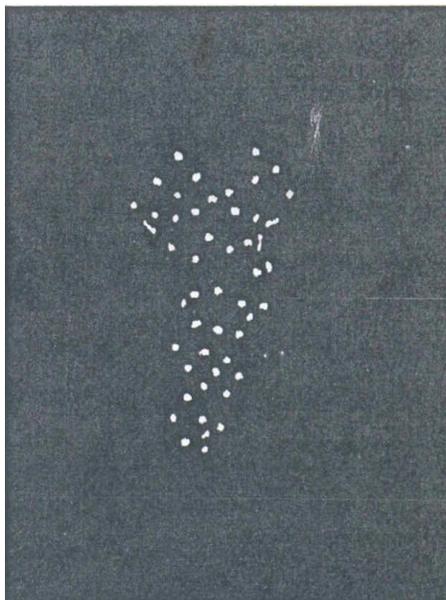Fig. 3. Location of berries in the contour of grape cluster

Fig. 4. Location of berries inside the grape cluster

5. Data Analysis

The NIR spectral data were analyzed using a commercial software package, GRAMS/32. First, the relative reflectance of each berry was calculated as the ratio of the difference in the absolute reflectance between the sample and the dark (no light) to that between the standard reference material and the dark. This relative reflectance (R) was then expressed as log(1/R). Each spectral curve was smoothed using the gap of 11 data points (or 22 nm). This gap was chosen after trial of several different gap sizes and was found to be adequate. The normalization method is often used to correct the spectra for indeterminate path-length when it cannot be measured. It was found that the normalization method gave slightly better prediction results and led to fewer factors in the statistical models. Therefore, only the results from the normalization method are reported in this article. After completing the above preprocessing procedures,

the partial least squares (PLS) method was used to develop calibration models for predicting the firmness and sugar content for the two grape varieties. The calibration models were developed using one half of the measured cherries from each variety, and the remaining half was used to validate the models.

5.1. Shape characterization

In order to characterize the shape of grape cluster, a method of calculation was used to define the following: 1) grape cluster elongation or widening which were handled with principal horizontal and vertical diameters (FY and FX) and the ratio of FX/FY, 2) global shape (rectangular, triangular,….) was handled with the relative position (DY) of the gravity center ordinate ($C_{grav}Y$) according to FY, 3) dissymmetry was handled with the relative position (DX) of the gravity center abscissa ($C_{grav}X$) according to FX as shown in **Fig. (5)**.
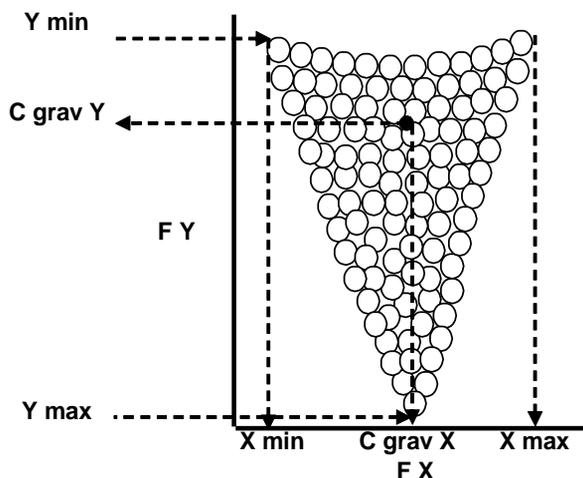

Fig. 5. Shape estimation

$FY = Y_{max} - Y_{min}$

$FX = X_{min} - X_{max}$

$DY = (C_{grav}Y - Y_{min}) / FY$

$DX = (C_{grav}X - X_{min}) / FX$

5.2. Berry size evaluation

Once arcs of circle corresponding to berries were isolated from the contour, a circle fitting is performed in order to estimate berries diameter. Some of the arcs isolated from the contour did not correspond to berries but to overlapping of two or three berries. In this case, berries diameter estimation could not be performed and a fitting coefficient was needed. The diameter estimation was not noted when the fitting coefficient was less than 0.9 (when the measured object did not correspond to a circle).

5.3. Calibration of Color

The color of each image was calibrated based on the images whose color had been already calibrated after the acquired images and transferred to the personal computer for image analysis. The detail of the color calibration procedure was indicated by **Hashimoto *et al* (2002)**. A standard image of grape cluster was chosen among the images acquired in the field, based on the fact that a good image should have a rare light unevenness around the parts of the chart for color calibration and the fruit cluster. The 3x3 matrices **C** and **C'** in Equation (1) denote the R, G, and B values of the chart in the standard image and of the sample image, respectively. Color transformation matrix **A** for the color calibration is calculated as follows.

$$A = C' \cdot C^{-1}$$ (1)

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \quad C = \begin{pmatrix} Rr & Gr & Br \\ Rg & Gg & Bg \\ Rb & Gb & Bb \end{pmatrix} \quad C' = \begin{pmatrix} R'r & G'r & B'r \\ R'g & G'g & B'g \\ R'b & G'b & B'b \end{pmatrix}$$

where, for example, R_g means the G value of the red chart.

The matrix **A** for each sample image was determined by using Equation (1). The color calibration image is obtained by multiplying the matrix **A** to the column vector of R, G, and B values corresponding to each pixel that composes the sample image:

$$\begin{pmatrix} r' \\ g' \\ b' \end{pmatrix} = A \cdot \begin{pmatrix} r \\ g \\ b \end{pmatrix}$$ (2)

where, r, g and b are R, G, and B values of a picture element of the sample image. r', g' and b' are R, G, and B values of the picture element after the color calibration.

RESULTS AND DISCUSSION

1. Image Processing

Stages of image processing were performed on all samples of grape cluster as follows:

- isolement of grape cluster
- isolement of peduncle
- isolement of porosity and contour
- extraction of general shape features such as principal diameters and center of gravity.

The obtained data showed that, 65.8% of arcs corresponding to berries were isolated from the contour of grape cluster. When neighboring berries overlapped or the arc was too small, critical points were detected because the curvature at this points was not high enough. This segmentation could be improved by taking into account other features of grape cluster contour such as vectorial product and distance between points of high curvature. Bad arc detection did not affect the diameter estimation because the removal of arcs presents a bad fitting coefficient. About 12% of specular reflexion rings detected were not berries for Superior variety. On the other hand, about 7% of specular reflexion rings detected were not berries for the King Ruby variety. That means, these errors was not constant and depended on the variety and were due to specular reflexion spots on the surrounding of the grape cluster.

2. Shape Characterization

The obtained data showed that, the calculation method was able to characterize the grape cluster elongation or widen-

ing. Grape cluster rather elongated presented FX / FY = 0.42 and widening grape cluster presented a FX / FY ≥1.98 for Superior variety and FX / FY = 0.51, FX / FY ≥1.88 for King Ruby variety respectively. Data also showed that, the general shape of grape cluster DY = 0.48 for rectangular grapes and DY = 0.32 for triangular grapes for Superior variety and DY=0.45, DY=0.31 for King Ruby variety respectively. Grape cluster dissymmetry were detected too, the symmetric grape cluster was DX = 0.49 and dissymmetric ones was DX = 0.57 for Superior variety and DX = 0.47, DX = 0.53 for King Ruby variety respectively. We also concluded that, high DX is not correlated with high dissymmetry.

This method is interesting to evaluate grape cluster elongation or widening with a continuous scale. It allows us to detect grape cluster dissymmetry but not its level because shape irregularity may need more descriptive methods to be evaluated. Berry diameter was measured for each grape cluster. The mean of measured berries was fitted by 2mm with the true measurements. The error was not serious if we consider the diameter variability inside the grape cluster or the bias occurred by sampling berries of the contour instead of the whole fruit.

3. ANN for Color Classification

The problem of color classification can thus be seen as a problem of determination of optimum edges capable of a suitable partition of an RGB color space. In order to fulfill these requirements, we propose the use of an artificial neural network (ANN) multilayer preceptor (MLP) trained by the back-propagation algorithm. For each new frame, the sys-

tem looks for a colored region (fruit) using the well-known region-growing algorithm **(Ballard and Brown 1982)**. Once located the fruit, the system is able to classify the pixels of the region and to analyze its color composition. The colors vectors found were compared with the previously stored patterns and the fruit was classified as belonging to the class that minimizes the distance from its color vector. After classification process, a visual indicator of the grape cluster class is added to the fruits pixels in the graphical interface as shown in **Fig. (6)**.

Fig. 6. A typical system of ANN for classified grape

4. Firmness Prediction

It would be helpful to examine how fiemness and sugar content are simply related to individual wavelengths so, a better understanding of NIR diffuse reflectance may be obtained. **Table (1)** summarizes the means and standard deviations (SD) of four measured quantities (maximum force, slope, area, and Brix reading) for both Superior and King Ruby varieties. On average, Superior variety was firmer than King Ruby one, as measured by the average maximum force (4.7 N vs. 3.9 N) and the slope of the force-deformation curves (1.4 N/mm vs. 1.2 N/mm). Superior have greater variations in the sugar content than King Ruby (SD = 1.9% vs. 1.5 %), although the average values for the two varieties were not statistically different.

Table (2) is a summary of the correlation coefficients among the three firmness indexes and sugar content for the two grape varieties. The three firmness indexes (force, slope, and area) were highly correlated with each other, with the correlation coefficients equal to, or greater

Table 1. Summary of means and standard deviations (SD) of three firmness indexes (force, slope, area) and brix reading for grape

Variety	Force (N)	Slope(N/mm)	Area(mm^2)	Brix (%)
Superior (n=450)	4.7 (1.2)	1.4 (0.5)	4.2 (1.2)	15.8 (1.9)
King Ruby (n=450)	3.9 (1.5)	1.2 (0.4)	3.9 (0.7)	15.2 (1.5)

The values in parentheses are the standard deviations (SD)

Table 2. Correlations among the measured firmness indexes and sugar content of Superior variety

	Force	Slope	Area	Brix
Force	1.00 (1.00)	0.99 (0.98)	0.96 (0.96)	-0.21 (-0.22)
Slope	0.96 (0.93)	1.00 (1.00)	0.98 (0.97)	-0.24 (-0.24)
Area	0.92 (0.88)	0.95 (0.94)	1.00 (1.00)	-0.26 (-0.24)
Brix	-0.23 (-0.21)	-0.24 (-0.23)	-0.25 (-0.22)	1.00 (1.00)

The values in parentheses are for King Ruby variety

than, 0.95 for Superior and between 0.87 and 0.96 for King Ruby. Because of the high inter-correlations among the three firmness indexes, further discussion of the results will focus on the maximum force. **Table (2)** also shows that the sugar content of grape was negatively correlated to the firmness indexes for both varieties, but the correlations were low, ranging between -0.21 and -0.26 for Superior and between -0.22 and -0.24 for King Ruby.

Figure (7) shows the average absorption spectral curves for three firmness classes (low, medium, and high) of Superior variety. Each class of grape was determined based on the maximum force measured with the Texture Analyzer. The fruit were considered low if the maximum force was less than 3.4 N, medium between 3.4 N and 6.2 N, and high if the force was greater than 6.2 N. This firmness classification is solely for gaining some qualitative understanding about the light absorption of grape as affected by fruit firmness, and it should not be considered a standard practice.

The absorption curves of grape were rather smooth across the entire spectral region and had three broadband peaks
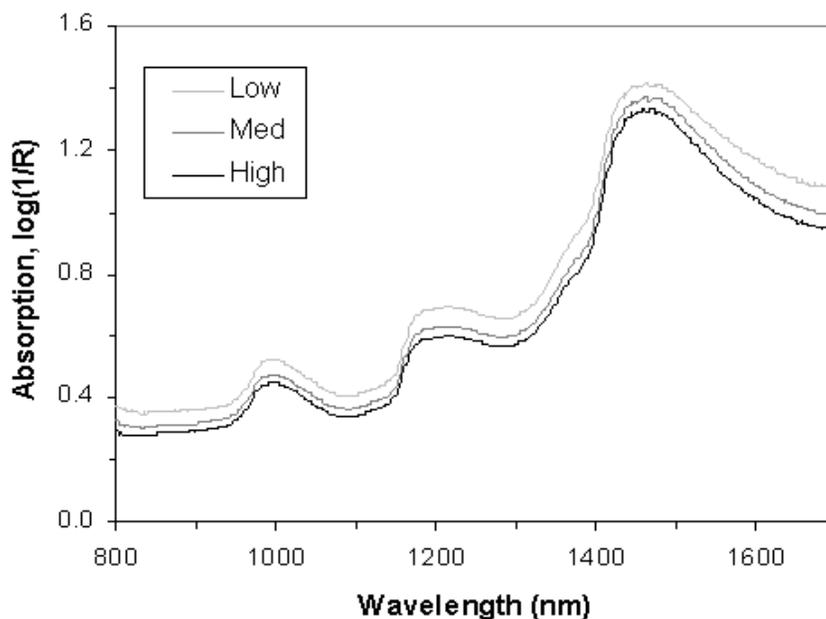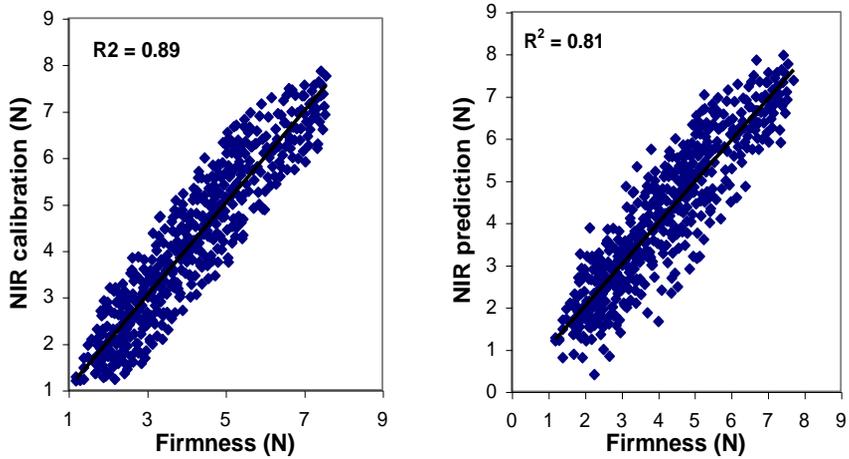
Fig. 7. Average absorption spectra of Superior for three firmness classes as measured by LFRA Texture Analyzer (2mm and 5mm depth) maximum force: low (F < 3.4 N), medium (3.4 N < F < 6.2 N), and high (F > 6.2 N). There were 100 fruit for the low class, 250 fruit for medium, and 100 fruit for high
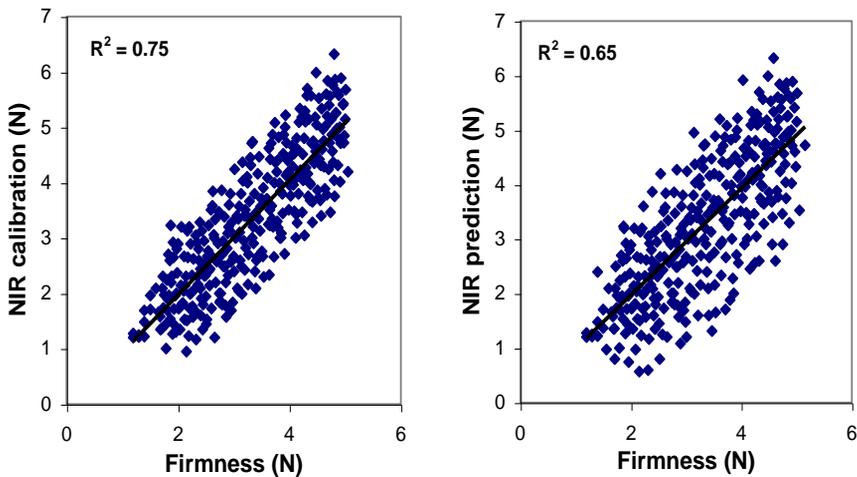
around 985 nm, 1174 nm, and 1469 nm as shown in **Fig. (7)**. These absorption peaks are rather close to the three absorption wavelengths of pure water (958 nm, 1153 nm, and 1460 nm) and, therefore, are related to the water in the grape fruit. As shown also in **Fig (7)**, the absorption of light decreased with fruit firmness. The firm fruit reflected more light (or absorbed less light) than softer fruit. The "low" firmness class of fruit had the highest average absorption, and the "high" class had the lowest average absorption across the entire spectral region between 800 nm and 1700 nm. Each

spectral curve did not cross over the other curves as shown in **Fig. (7)**. The same pattern of light absorption with fruit firmness which observed for King Ruby was almost the same as in **Renfu (2001)**.

Figure (8) shows the calibration and prediction results of firmness from the calibration models for Superior and King Ruby varieties. The correlation of calibration between NIR measurements and the maximum force for Superior variety was as high as 0.89, with the standard error of calibration (SEC) of 0.51 N. When the model was used to predict the other half of the data, prediction results were also

(a) Superior variety

(b) King Ruby variety

Fig. 8. NIR calibration and prediction results from the partial least square models for the firmness of (a) Superior and (b) King Ruby

good (r = 0.81 and SEC = 0.69 N). The calibration model appeared to be robust since only five factors were used in the calibration model. Similar results were obtained when NIR spectral data were used to predict the slope and area of the force-deformation curves.

For King Ruby fruit, the calibration model for firmness had only four factors. The correlations of calibration and prediction between NIR spectral data and the maximum force were 0.75 and 0.65, respectively, which are lower than those for Superior. The SEC and SEP for King Ruby were 0.39 N and 0.44 N, respectively, which are better than those for Superior. If the coefficient of variance (CV) was used as a measure of calibration and prediction errors, then the differences between the two varieties were small. These results indicate that NIR diffuse reflectance can be used to predict the firmness of grape fruit with reasonable accuracy.

5. Sugar Content Prediction

Figure (9) shows three average absorption spectral curves for Superior grouped into three classes based on their Brix readings (**Renfu, 2001**). A grape was considered "low" if its Brix reading was less than 11 %, "medium" between 11 % and 16 %, and "high" greater than 16 %. Again, the grouping method was solely for helping us in gaining some qualitative understanding of the overall trend of the light absorption in fruit as affected by its sugar content. A consistent pattern of the light absorption in fruit with respect to sugar content is observed from **Fig. (9)**. The average light absorption in fruit increased with its sugar content; the "high" class of Superior have the highest average absorption of light and the "low" class had the lowest absorption for the spectral regions between 800 nm and 1700 nm and the result was the same as in **Renfu (2001)**.
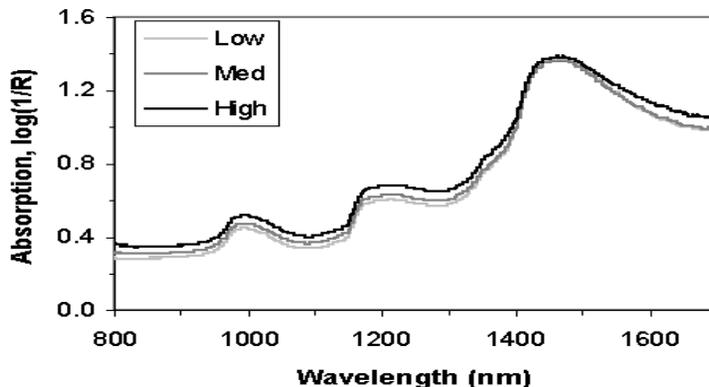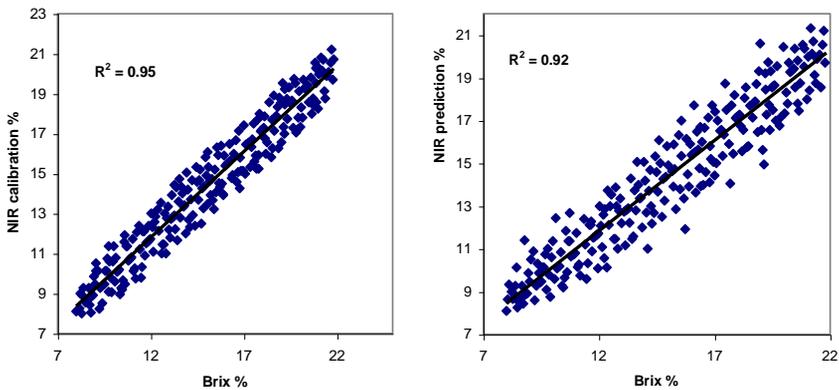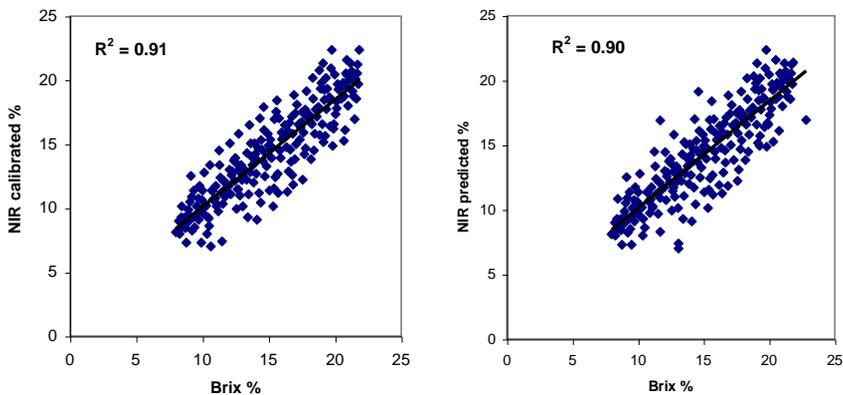

Fig. 9. Average absorption spectra of Superior for three sugar content levels: low (Brix < 11.0 %), medium (11 % < Brix < 16 %), and high (Brix > 16 %). There were 100 fruit for the low class, 250 fruit for medium, and 100 fruit for high

The calibration models gave excellent fits to the Brix data for both Superior and King Ruby varieties as shown in **Fig. (10)**. The correlation for the calibration model for Superior fruit was 0.95 and the SEC was 0.52 % Brix. When the model was used to predict the sugar content of the prediction data set for Superior variety, the prediction errors increased slightly, with r = 0.92 and SEP = 0.71 % Brix. For King Ruby variety, the correlation of calibration was 0.91 and the SEC was 0.65 % Brix, on the other hand, prediction data set was 0.90 and SEP was 0.61% Brix. These results indicate that the sugar content of grape can be accurately predicted using NIR diffuse reflectance.

(a) Superior variety

(b) King Ruby variety

Fig. 10. NIR calibration and prediction results from the partial least square models for the sugar content of (a) Superior and (b) King Ruby

CONCLUSIONS

An image analysis method was implemented. This image processing allowed to extract grape features essential for shape evaluation, berry diameter and grape compactness evaluation. The method was efficient to measure the elongation or widening of grape with a continuous scale. Dissymmetry or shape irregularity might need more descriptive methods to be evaluated. The results of this study also showed that there were relatively good correlations of prediction between NIR measurements and firmness for the two varieties of grape, with a correlation of 0.80 and standard error of prediction (SEP) of 0.55 N for Superior, and r = 0.65 and SEP = 0.44 N for King Ruby. The NIR model based on the partial least square method gave good predictions of the sugar content of cherries (r = 0.97 and SEP = 0.71 % Brix for Superior, and r = 0.89 and SEP = 0.65 % Brix for King Ruby). These results are very encouraging and indicate that NIR diffuse reflectance between 800 nm and 1700 nm can be used to predict the firmness and sugar content of grape with reasonable accuracy.

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استخدام التقنية الحديثة فى فحص وفرز العنب

[36]

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1- معهد بحوث الهندسة الزراعية – شارع نادى الصيد – الدقى – الجيزة – مصر

يعتبر العنب من أهم محاصيل الفاكهة الثانى بعد محصول الموالح فى مصر. حيث تبلغ مساحته المنزرعة حسب أخر أحصائية لوزارة الزراعة152488 فدان تنتج حوالى مليون و 73815 طن من العنب. ومن أهم أصناف العنب المنزرعة فى مصر هما صنفى السوبيريور (البناتى الاصفر) و كنج روبى (البناتى الاحمر) حيث يمثل هذان الصنفان 50% من المساحة المنزرعة فى مصر من العنب. كما يعتبر فحص وفرز العنب فى مصر والعالم من أهم العوامل التى يجب أن تراعى أثناء التداول أو التصدير.

فى هذه الدراسة تم استخدام خاصية انعكاس الاشعة تحت الحمراء بطول موجى يتراوح بين 800 nm و 1700 nm كتقنية حديثة لمعرفة درجة اللون ودرجة الصلابة لحبة العنب وكذلك المحتوي السكرى فى العنب. كما تم الاستعانة أيضا ببرامج اللون RGB وبرنامج الشبكات العصبية ANN كمرجع لهذة الدراسة.

وقد أثبتت النتائج أنه باستخدام هذة التقنية الحديثة فقد تم الوصول الى معرفة الحجم والطول والعرض واللون الحقيقى لعنقود العنب. كما أيضا تم تحديد درجة صلابة حبة العنب وكذلك تقدير نسبة السكر فى العنب لصنفى سوبيريور و كنج روبى.

بالنسبة لدرجة صلابة حبة العنب فقد وجد أن معامل الارتباط 0.8 مع مقدار خطأ فى التبؤ 0.55 نيوتن لصنف سوبيريور مقارنة بالنتائج المتحصل عليها بالقياس على جهاز تحليل الصلابة .أما بالنسبة لصنف كنج روبى فقد وجد أن معامل الارتباط 0.65 مع مقدار خطأ فى التنبؤ 0.44 مقارنة بالنتائج المتحصل عليها بالقياس على جهاز تحليل الصلابة.

أما بالنسبة لدرجة تقدير المحتوى السكرى للعنب فقد وجد أن معامل الارتباط 0.97 مع مقدار خطأ فى التنبؤ 0.71% بركس لصنف سوبيريور مقارنة بالنتائج المتحصل عليها بالقياس على جهاز تحليل المحتوى السكرى .أما بالنسبة لصنف كنج روبى فقد وجد أن معامل الارتباط 0.89 مع مقدار خطأ فى التنبؤ 0.65% بركس مقارنة بالنتائج المتحصل عليها بالقياس على جهاز تحليل المحتوى السكرى.